Submovements

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Outline

Intermittent control
- Optimal feedback control

Models

Number of submovements

Neural correlates

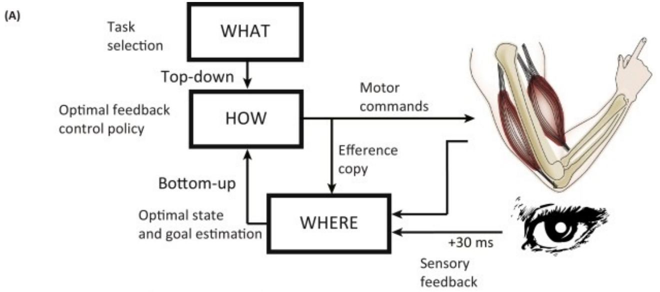
Motor disorders

Analyses

Practical

Optimal feedback control

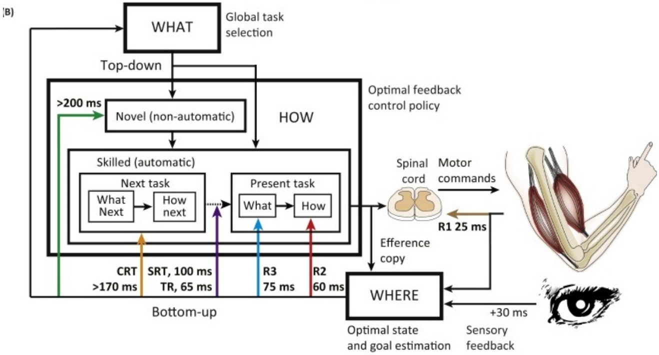
- The dominant theory for movement generation is optimal feedback control [Todorov and Jordan, 2002], where a controller generates the movement and can control for disturbances



From Scott [2016]

Optimal feedback control

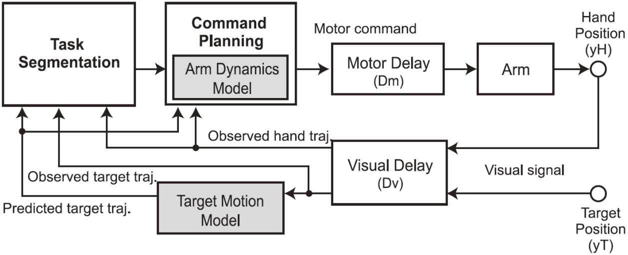
- These models need to take into account the multiple types and timescales of feedback



From Scott [2016]

Intermittent control

- Intermittent control has been suggested as a way of dealing with feedback delays [Navas and Stark, 1968, Miall et al., 1993, Burdet and Milner, 1998, Morasso et al., 2010, Gawthrop et al., 2011]
- In addition, intermittent control is more robust (i.e., it guarantees stability in a larger region of the control parameter space)

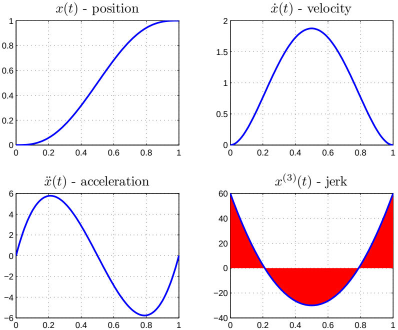


From Sakaguchi et al. [2015]

OUTLINE

Submovements

- If we assume that intermittent control is being used, what are the "building blocks" of movement?
- Bell-shaped velocity profiles are a landmark features of human / biological movement
- One popular model is the minimum jerk model [Flash and Hogan, 1985], which predicts maximally smooth trajectories



SUBMOVEMENTS

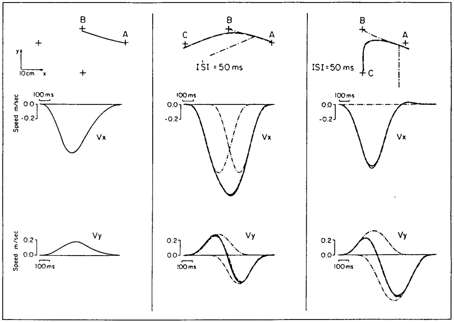
- In reality, submovements are not symmetrical - Plamondon et al. [1993] tested 23 types of movements, and found that support-bounded lognormal movements best modelled straight line movements

$$B(t) = \frac{D(T_1 - T_0)}{\sigma\sqrt{2\pi}(t - T_0)(T_1 - t)} \exp\left\{\left(\frac{-1}{2\sigma^2}\right)\left[\ln\left(\frac{t - T_0}{T_1 - t}\right) - \mu\right]^2\right\}$$

- D = displacement
- $T_0 \leq t \leq T_1$
- μ controls the skewness (asymmetry)
- σ determines the kurtosis (“fatness”)

SUPERPOSITION

- When there are multiple submovements, we can simply add them together (vector superposition) [Flash and Henis, 1991, Doeringer and Hogan, 1998, Sosnik et al., 2004, Friedman and Korman, 2019]
- Note that one submovement does not need to finish before the next submovement starts



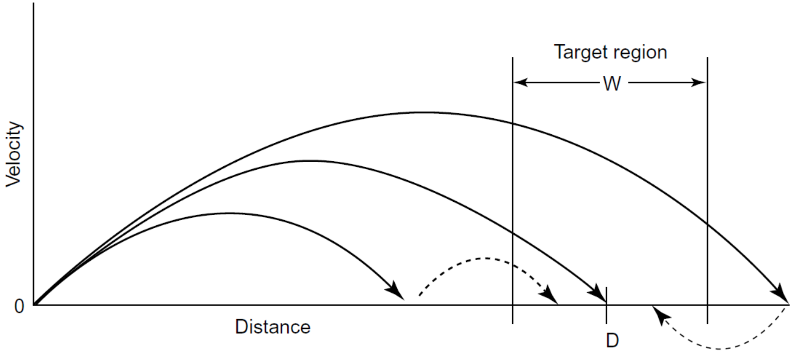
Dynamic movement primitives

- The submovements we have can described can be considered as a dynamic primitive of movement [Schaal, 2006, Hogan and Sternad, 2012, Ijspeert et al., 2013], where there is an attractor
- We have so far been examining discrete submovements, another formulation is needed for rhythmic movements

OUTLINE

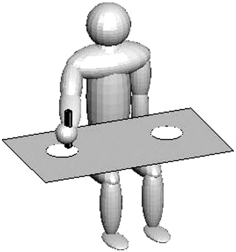
WHY MULTIPLE SUBMOVEMENTS?

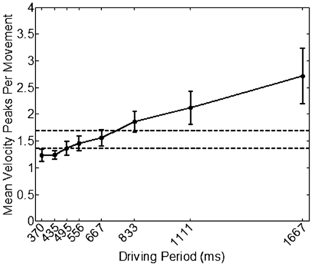
- This naturally leads to the question of why we make multiple submovements instead of just one submovement?
- The model of Meyer et al. [1988] predicts well performance in speeded reaching to a target when spatial accuracy is imperfect, and a trade-off is made between distance and speed



WHY MULTIPLE SUBMOVEMENTS?

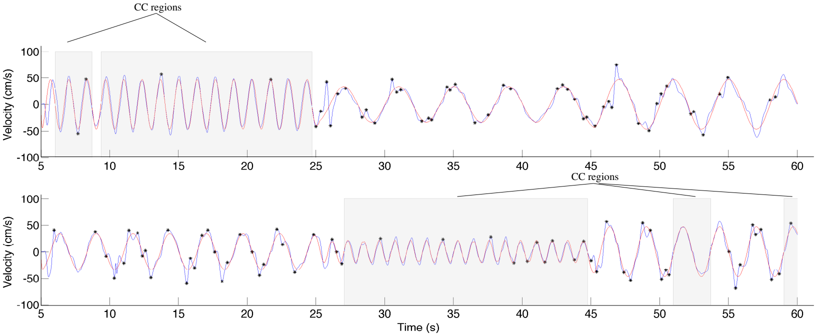
- In Fradet et al. [2008], they found that submovements are not only performed when approaching a target, but also due to movement speed
- If we look at slow movements, we always see lots of submovements [van der Wel et al., 2009]





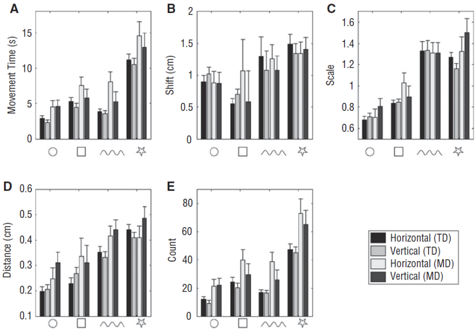
Why multiple submovements?

- We are not able to make slow, smooth movements - below a threshold, we start to produce multiple submovements [Park et al., 2017, Noy et al., 2017]



WHY MULTIPLE SUBMOVEMENTS?

- In long duration movements, there is typically a strong correlation between movement time and number of submovements [Portnoy et al., 2018]



Outline

Neural correlates of submovements

- There have been some studies showing neural correlates of submovements
- For example, in macaques there are neurons that seem to code for the second submovement in a double-step paradigm [Dickey et al., 2013]

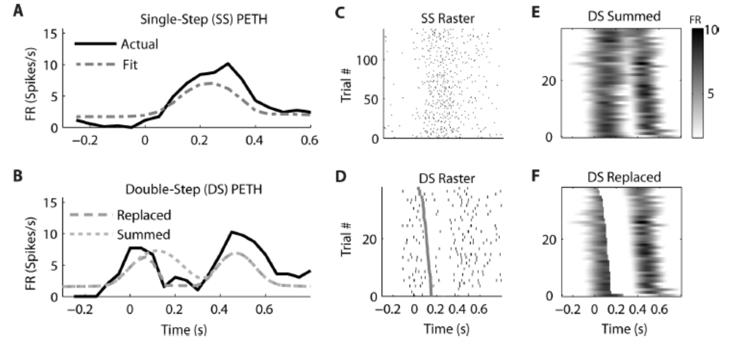
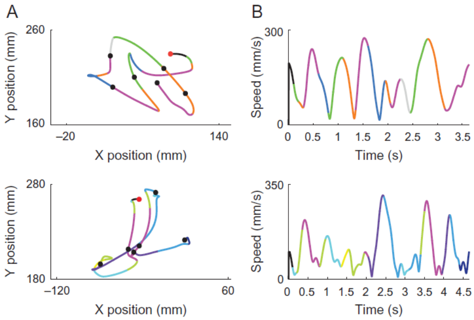


FIGURE 8 | A neuron from dorsal premotor cortex is better fit by the "Replaced" hypothesis. Format follows **Figure 5**.

Neural correlates of submovements

- Single cell recordings using Hidden Markov models showed that there are transitions that are associated with acceleration and deceleration epochs [Kadmon Harpaz et al., 2019]



Neural correlates of submovements

- In an EEG study, an ERP component was found that was time-locked to submovement onset [Pereira et al., 2017]

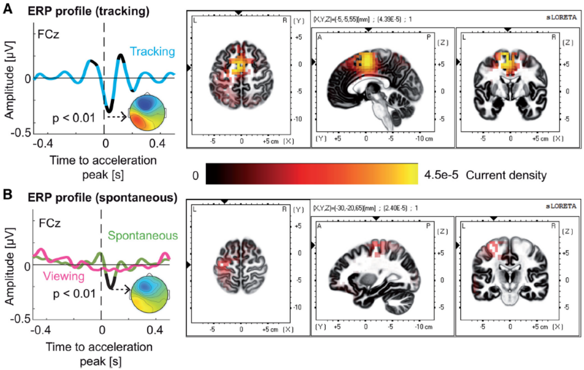
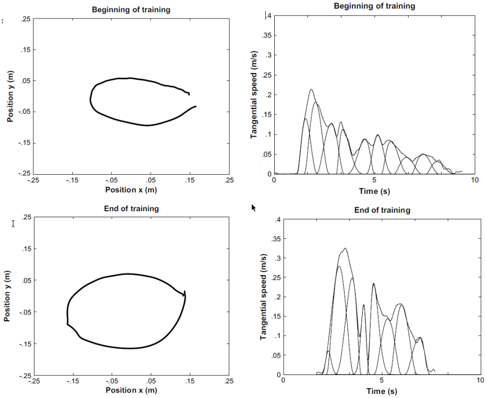


Figure 2. ERP time-locked to submovements ***A***, The ERP time-locked to submovements for the tracking (cyan trace) conditions, averaged across subjects. The ERP showed a significant trough localized in the medial frontal gyrus (right inset). Significant portions of the ERP are shown in black ($p < 0.01$, Bonferroni corrected). ***B***, The ERP time-locked to hand acceleration for the spontaneous (green trace) and viewing (magenta trace) conditions, averaged across subjects. During the spontaneous condition, the ERP showed a significant trough (black segment, $p < 0.01$, Bonferroni corrected), localized in the left (contralateral) precentral gyrus. The ERP for different directions of the target (orange for north, blue for east, purple for south and yellow for west; see inset) can be found in Extended Data Figure 2-1. No discernible differences in ERP amplitude were observed.

Outline

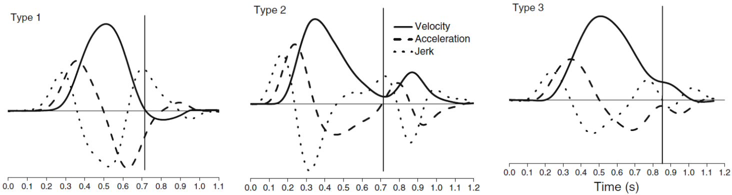
MOTOR DISORDERS

- In people recovering from stroke, submovements have been observed to decrease in number and become more overlapped [Dipietro et al., 2014, 2009, Rohrer et al., 2004]



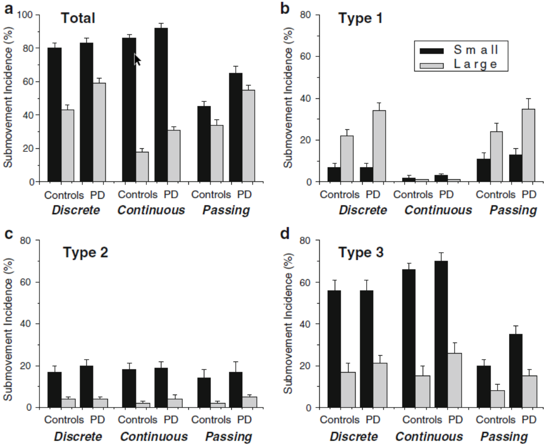
Parkinson's disease

- Dounskaia et al. [2009] compared how three different types of submovements are used, comparing older adults to people with Parkinson's disease



Parkinson's disease

- The types of submovements used varied between controls and people with PD



Outline

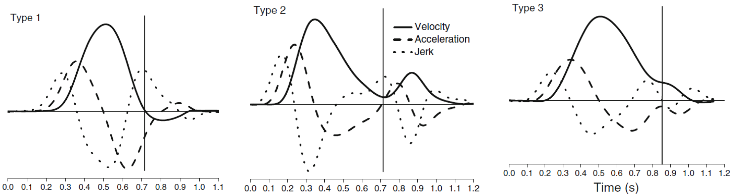
Types of analyses

There are a number of different types of analyses that can be performed on submovements:

- Using submovements as a smoothness measure (e.g. number of peaks) - need to be careful of confound of movement time

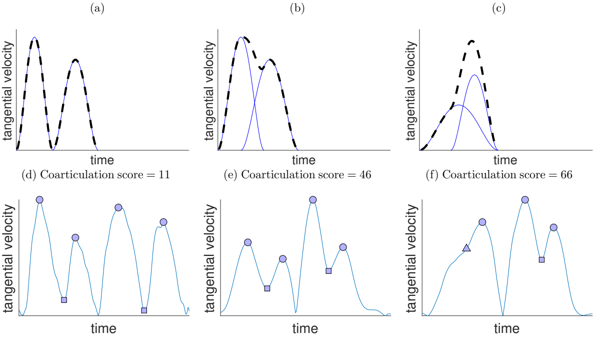
Types of analyses

- Identifying types of submovements used (as in the papers of Meyer et al. [1988], Dounskaia et al. [2009])



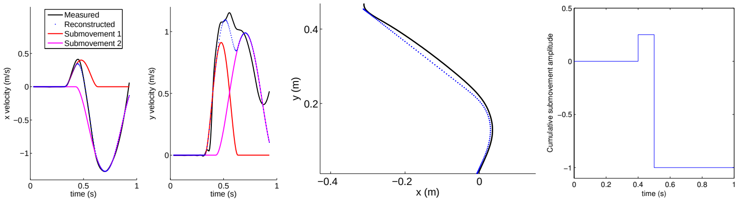
Types of analyses

- Using overlap of submovements as a measure of coarticulation [Sosnik et al., 2004, Friedman and Korman, 2019, Sporn et al., 2020]

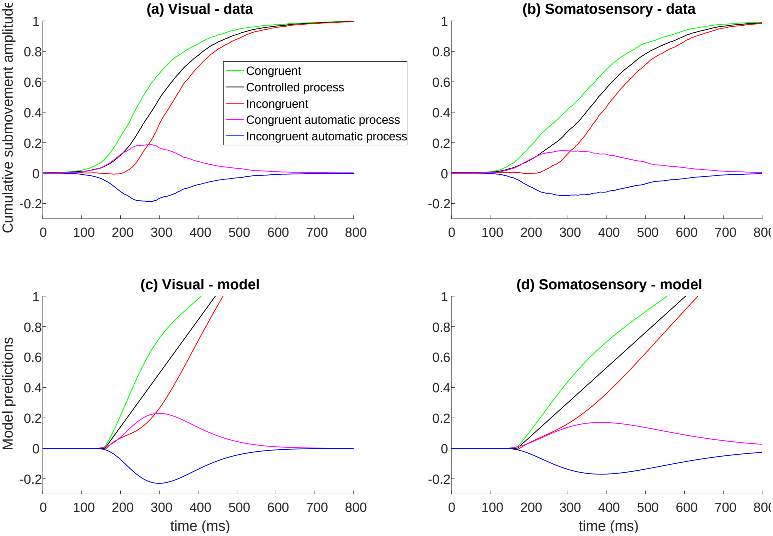


TYPES OF ANALYSES

- Reaching movements can be decomposed into their constituent submovements [Friedman et al., 2013, Salzer and Friedman, 2020]

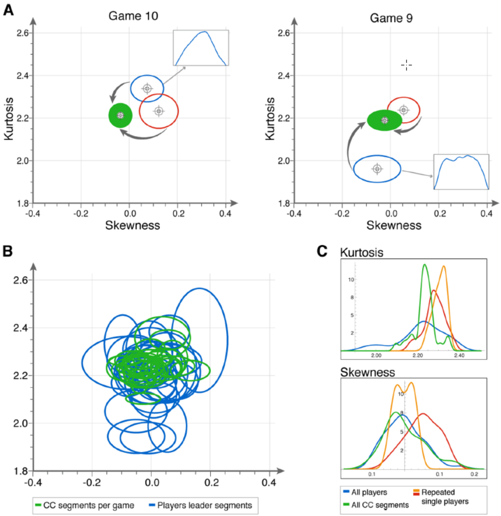


Types of analyses



Types of analyses

- Submovements can be classified according to their shape (skew / kurtosis) [Hart et al., 2014]



CONCLUSIONS

- There is significant kinematic, modeling and neurophysiological evidence that we make use of intermittent movements
- Regardless of the origin of submovements, they are a useful tool for analyzing kinematic data, including:
  - Understanding movement strategies
  - Tracking progress of learning
  - Quantifying rehabilitation
  - Decomposing movement intent

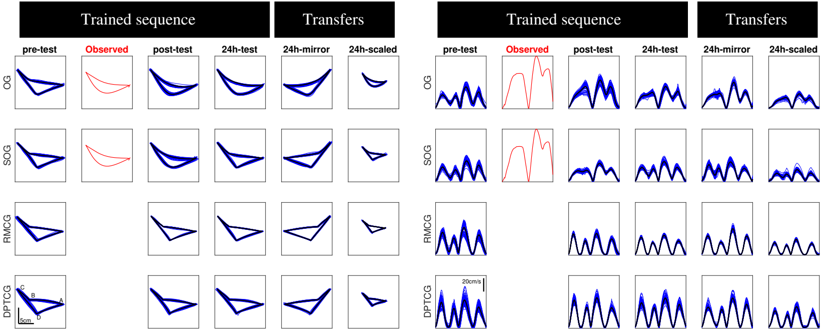
Outline

PRACTICAL EXERCISE

The matlab code and data needed for the exercise can be found online. An example solution is also available on the website. If you have any corrections, suggestions or a different solution, please send it to me!

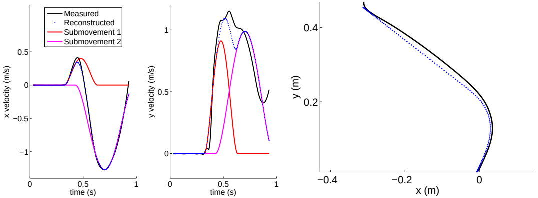
Practical exercise

- In this example, we will decompose movements from a drawing task [Friedman and Korman, 2019]



DECOMPOSITION

- We assume that each submovement is a minimum jerk submovement
- We use a method similar to the technique described in Rohrer and Hogan [2006]
- The cost function is the difference between the superposition of the submovements, and the actual velocity profile



Decomposition

- We also include a term for the tangential velocity, to prevent the optimization from selecting two approximately simultaneous submovements with large but opposite velocities
- We start with 10 random guesses, and use an optimization technique to find the best minimum jerk parameters that describe the data (i.e., minimize the cost function)

$$\sum_t \frac{(F_x(t) - G_x(t))^2 + (F_y(t) - G_y(t))^2 + (F_v(g) - \sqrt{G_x(t)^2 + G_y(t)^2}))^2}{2(G_x(t)^2 + G_y(t)^2)}$$

Goal

- The goal of the session is to decompose the movements for two subjects into submovements, and calculate some relevant measures
- The matlab code can be copy / pasted into your Matlab session
- There are questions to answer based on running the code

Step 1: Download the data

```
websave('master.zip',...
['https://github.com/JasonFriedman/submovements/' ...
'archive/refs/heads/master.zip']);
unzip('master.zip');
% Change into the directory
cd('submovements-master');
% Add the code directory to the path
addpath('matlab');
```

Step 2: Load the data

- This subject is from the double physical practice control group

```
[position,velocity,time] = ...
    loaddata('data/subject08day1pre/');
```

Step 3: Plot the data to become familiar with it

```
plotposition(position,time);
plotvelocity(velocity,time);
```

- Q: How many movements are there?
- Q: What are the units likely to be?
- Q: How long did the movements take (mean / std)?

Step 4: Decompose a single trial into 4 submovements

```
numsubmovements = 4;

xrng = [-20 20];
yrng = [-10 10];

k=1;
[bestError1,bestParameters1,bestVelocity1] = ...
 decompose2D(time{k},velocity{k},numsubmovements,...
 xrng,yrng);
```

- Q: how many parameters are there in total?
- Q: What are the units of the parameters?

Step 5: Plot the result

```
% velocity
figure;
plotSubmovements2D(bestParameters1,time{k},1);
hold on;
plot(time{k},velocity{k});

% position
figure;
x0 = position{k}(1,1);
y0 = position{k}(1,2);
plotSubmovements2D(bestParameters1,time{k},3,x0,y0);
hold on;
plot(time{k},position{k}(:,1),'b--','LineWidth',2);
plot(time{k},position{k}(:,2),'r--','LineWidth',2);
```

Step 5: Plot the result

```
% position x vs y
figure;
plotSubmovements2D(bestParameters1,time{k},5,x0,y0);
hold on;
plot(position{k}(:,1),position{k}(:,2),'b--',...
 'LineWidth',2);
```

- Q: How well did the reconstruction match the original movement and does this differ for position and velocity. Why?

Step 6: Run the decompisition on all trials in the condition

```
% Get a coffee while you are waiting
for k=1:numel(time)
  k
  [bestError(k),...
  bestParameters(k,:),...
  bestVelocity{k}] = ...
   decompose2D(time{k},velocity{k},numsubmovements,...
   xrng,yrng);
end
```

Step 7: Plot the parameters as a function of time

```
parameterNames = {'t0','D','Ax','Ay'};

figure;
for submovement=1:4
 for parameter=1:4
  subplot(4,4,(submovement-1)*4+parameter);
  plot(bestParameters(:,(submovement-1)*4+parameter));
  if submovement==4
   xlabel('trial');
  end
  title([parameterNames{parameter} ' ' ...
   num2str(submovement)]);
 end
end
```

- Q: What trends can you observe in the data?

Step 8: Calculate two new parameters based on the decomposition

```
% overlap and relative onset time
%
% overlap: mean percent overlap between
% two submovements
overlapsPre = calculateOverlap(bestParameters);

% relative onset time: time 2-4th submovement
% starts relative to duration of previous
% submovement

relativeOnsetsPre  = ...
    calculateRelativeOnset(bestParameters);
```

Step 9: Run the decomposition on the posttest and compare to the pretest

```
[positionPost,velocityPost,timePost] = ...
    loaddata('data/subject08day1post/');
% (get another coffee!)
for k=1:numel(timePost)
    k
    [bestErrorPost(k),...
     bestParametersPost(k,:),...
     bestVelocityPost{k}] = ...
      decompose2D(timePost{k},velocityPost{k},...
      numsubmovements,xrng,yrng);
end

overlapsPost = calculateOverlap(bestParametersPost);
relativeOnsetsPost  = ...
    calculateRelativeOnset(bestParametersPost);
```

- Q: Is there a difference between the pre and post?

Step 10: Compare results to a subject from the observation group

```
[positionPre2,velocityPre2,timePre2] = ...
    loaddata('data/subject34day1pre/');
% (get another coffee!)
for k=1:numel(timePre2)
     k
     [bestErrorPre2(k),...
      bestParametersPre2(k,:),...
      bestVelocityPre2{k}] = ...
        decompose2D(timePre2{k},velocityPre2{k},...
        numsubmovements,xrng,yrng);
end

overlapsPre2 = calculateOverlap(bestParametersPre2);
relativeOnsetsPre2  = ...
    calculateRelativeOnset(bestParametersPre2);
```

Step 10: Compare results to a subject from the observation group

```
[positionPost2,velocityPost2,timePost2] = ...
    loaddata('data/subject34day1post/');
% (get another coffee!)
for k=1:numel(timePost2)
 k
 [bestErrorPost2(k),...
  bestParametersPost2(k,:),...
  bestVelocityPost{k}] = ...
   decompose2D(timePost2{k},velocityPost2{k},...
   numsubmovements,xrng,yrng);
end

overlapsPost2 = ...
    calculateOverlap(bestParametersPost2);
relativeOnsetsPost2  = ...
    calculateRelativeOnset(bestParametersPost2);
```

Step 10: Compare results to a subject from the observation group

- Q: What are the differences between the subjects from the two groups? What does this suggest about differences in coarticulation between the groups? (Disclaimer: A proper analysis would of course look at all subjects and use an appropriate statistical test!)

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